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WEAR STATE DISCONTINUOUS TRACKING MODEL AS TWO-LAYER PERCEPTRON WITH NONLINEAR TRANSFER FUNCTIONS BEING TRAINED ON AN EXTENDED GENERAL TOTALITY REGARDING STATISTICAL DATA INACCURACIES AND SHIFTS

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There is presented a framework for tracking metal tool wear states discontinuously, when the states' finite set has been statistically tied to the set of representative wear influencing factors. Range of wear states is presumed to be wholly sampled into those factors. The tracker is two-layer perceptron with nonlinear transfer functions. It is a static model, unlike evolutionary dynamic models of forecasting wear. Its identification starts with forming the initial finite general totality containing correspondence between influencing factors and each known wear state. Two-layer perceptron is then trained on an extended general totality, whose elements are sum of pure representatives and normal variates' values in two terms. The first term models jitter inaccuracies and omissions in statistical data or measurements. The second term models possible shifts of wear influencing factors' values in every state. The identification final stage is the input of two-layer perceptron is re-fed with the pure representatives for making sure that they have not been disassociated from the initially given wear states. It is said also about liable and easy realizability of the tracking model. When range of wear states embraces all practiced wears, the presented two-layer perceptron tracker will control metal tool object wear states with minimized error, ensuring negligibility of underuse or overuse of materials.

Key words: wear state, tracking model, statistical data, two-layer perceptron, training, identification, tracking error rate, data jitter inaccuracies, data omissions, data shifts.

Importance of tracking wear states

Tracking metal wear states reliably is necessary for preventing underuse and overuse of metal tools, details, mechanisms, manufacture, etc. If wear is overestimated then it causes underuse. Overuse is consequence of underestimated wear. It is clear that overestimation and underestimation are unavoidable. However, if a metal object wear states are tracked with minimized error then result of underuse or overuse is negligible. This negligibility means rationalized usage of metal resource, what is desired in working.

Approaches to problem of tracking wear states

Mathematically, there are two generalized approaches to problem of tracking wear states. One of them allows to track wear continuously, using differential equations [1] for describing how wear values vary against time and influence of other factors, including geometrical coordinates, pressure, temperature, etc. Sometimes, these equations contain stochastic components [2]. Rarer, the tracker is regression. The second approach proposes to control a finite set of wear states. It can be either a finite difference method or a method of statistical correspondence [3]. While wear is tracked discontinuously, its neighboring states are close either by wear factual values or by values of factors influencing on wear. Closure by wear factual values is not typical for statistical correspondence methods, aiming at linguistic description (for instance, having states "worn lightly", "worn moderately", "worn badly", "worn ultimately", and so on). Particularly, this is about neural networking with multiple variables (influencing factors).

Whatever approach is, it needs statistical data. For tracking wear continuously, the data is accumulated for setting up initial and boundary conditions in differential and difference equations [1, 3]. But in the course of time their coefficients are required to be re-determined [2]. Generally, accuracy of the continuity approach is decreasing [1, 3] as time goes by. To the contrary, the averaged accuracy of neuronet methods is maintained constant through the whole range of wear states. The accuracy rank is dependent on the initial statistical data. However, we need fast and confident neuronet identification methods to make the rank as high as possible. This is especially urgent when the number of influencing factors is of the order of tens [1]. Besides, sufficient amount of statistical data is not always available.

Goal

For a finite statistical data set, containing correspondence between influencing factors and each known wear state, we are to develop a framework of tracking those states. The tracker model is a two-layer perceptron with nonlinear transfer functions (2LPNLTF). This is a universal classifier [4]. Its finite general totality (FGT) is given in those correspondences. The major task is to substantiate the transition from that FGT to an extended general totality (EGT), whose cardinality would be sufficient to identify 2LPNLTF classifier at the proper rank. An expected gain is simplicity of the identification. Note that inasmuch as the tracker is 2LPNLTF then the classifier high operation speed is presumed.

Tracking wear states with 2LPNLTF

Let $\mathbf{X}_j = \left[x_i^{\langle j \rangle} \right]_{1\times Q} \in X \subset \mathbb{R}^Q$ be the j-th group with $Q \in \mathbb{N}$ wear influencing factors (WIF), corresponding to the wear state $w_j \in W \subset \mathbb{R}$. As the set $W \subset \mathbb{R}$ is finite then, without loss of generality, we can state that $w_j \in \left\{ \overline{1, N} \right\}$ by number $N \in \mathbb{N} \setminus \{1\}$ of total states. FGT is

$$\left\{ \left\{ \mathbf{X}_j ,\, w_j \right\} :\, j = \overline{1, L},\, L \in \mathbb{N} \setminus \left\{ \overline{1, N-1} \right\},\, \forall\, s = \overline{1, N}\ \exists\, j_s \in \left\{ \overline{1, L} \right\} \Rightarrow \left\{ \mathbf{X}_{j_s} ,\, w_{j_s} \right\} \in \left\{ \mathbf{X}_j ,\, w_j \right\}_{j=1}^{L} \right\}. \tag{1}$$

Formally, the problem is to find a map $\psi_* \in \Psi$ of the set $X \subset \mathbb{R}^Q$ into the set $W = \left\{ \overline{1, N} \right\}$ such that

$$\psi_* \in \arg\min_{\psi \in \Psi} \sum_{\mathbf{X}_0 \in X_0 \subset X} \operatorname{sign} \left| w_0 - \psi\left(\mathbf{X}_0 \right) \right| \quad \forall\, X_0 \subset X \tag{2}$$

by correspondence of WIF $\mathbf{X}_0 \in X$ to the state $w_0 \in W$.

The single object input of 2LPNLTF is $\mathbf{X} = \left[x_i \right]_{1\times Q} \in X$ and the output of 2LPNLTF is the number

$$s_* \in \arg\max_{s=\overline{1, N}} \left\{ \left(1 + \exp\left[-\left(\sum_{k=1}^{S_{\text{SHL}}} u_{ks} \cdot \left(1 + \exp\left[-\left(\sum_{i=1}^{Q} x_i a_{ik} + h_k \right) \right] \right)^{-1} + b_s \right) \right] \right)^{-1} \right\} \tag{3}$$

of the current wear state. With S_{SHL} neurons in the single hidden layer (SHL) of 2LPNLTF, the problem (3) contains $S_{\text{SHL}} \cdot \left(Q + N + 1 \right) + N$ coefficients

$$\left\{ \left[a_{ik} \right]_{Q\times S_{\text{SHL}}} ,\, \left[u_{ks} \right]_{S_{\text{SHL}}\times N} ,\, \left[h_k \right]_{1\times S_{\text{SHL}}} ,\, \left[b_s \right]_{1\times N} \right\} \tag{4}$$

to be determined for the map in (2): matrix $\left[a_{ik} \right]_{Q\times S_{\text{SHL}}}$ of weights in SHL, matrix $\left[u_{ks} \right]_{S_{\text{SHL}}\times N}$ of weights in the output layer, vector $\left[h_k \right]_{1\times S_{\text{SHL}}}$ of SHL biases, vector $\left[b_s \right]_{1\times N}$ of the output layer biases. In fact, the map $\psi_* \in \Psi$ in (2) is realized as (3), being the function $w = \psi_*\left(\mathbf{X} \right)$ by $w = s_* \in W$. Coefficients (4) are determined through the process of their updating. This is the identification process, allowing to solve the problem (2) via training 2LPNLTF (3).

The training process starts by feeding the input of 2LPNLTF with the training set

$$\left\{ \mathbf{Y} = \left[y_{is} \right]_{Q\times N} :\, y_{is} = x_i^{\langle j_s \rangle} \right\} \tag{5}$$

and getting the coefficients (4) updated according to the pure representatives (5) of those N states. For (5), the identifier is $N \times N$ identity matrix $\mathbf{I}$. Then 2LPNLTF is trained by feeding its input with the training set regarding possible noises and inaccuracies in statistical data or measurements. As wear is influenced with a great deal of factors (which, upon the whole, are innumerable), then those noises must be treated as normal. Also statistical data may be shifted as a result of systematic inaccuracies and methodological poorness. Eventually, some data are sometimes omitted. Omissions occur in consequence of that not all WIF $\left\{ x_i \right\}_{i=1}^{Q}$ in $\mathbf{X}$ can be accurately measured or assigned. So let $\mathcal{N}\left(0, 1 \right)$ be infinite set of normal variate's values with zero expectation and unit variance. After the training process first stage with (5) is complete, there comes the second stage. The input of 2LPNLTF is fed with the training set

$$D\left(R, H, \sigma_0, \mu \right) = \left\{ \left\langle \left\{ \mathbf{Y} \right\}_{r=1}^{R} ,\, \left\{ \tilde{\mathbf{Y}}_h \right\}_{h=1}^{H} \right\rangle :\, \mathbf{Y} = \left[y_{is} \right]_{Q\times N} ,\, y_{is} = x_i^{\langle j_s \rangle} ,\, R \in \mathbb{N} \cup \{0\},\right.$$

$$\tilde{\mathbf{Y}}_h = \mathbf{Y} + \sigma_h \cdot \mathbf{\Xi} + \mu \cdot \sigma_h \cdot \mathbf{\Theta},\, \sigma_h = h \sigma_0 H^{-1}\ \forall\, h = \overline{1, H},\, H \in \mathbb{N},$$

$$\left. \sigma_0 > 0,\, \mathbf{\Xi} = \left[\xi_{is} \right]_{Q\times N} ,\, \xi_{is} \in \mathcal{N}\left(0, 1 \right),\, \mu > 0,\, \mathbf{\Theta} = \left[\theta_{is} \right]_{Q\times N} ,\, \theta_{is} = \zeta_s \in \mathcal{N}\left(0, 1 \right) \right\} \tag{6}$$

and getting the coefficients (4) updated according to identifiers $\{\mathbf{I}\}_{u=1}^{R+H}$. While training, validation is executed by feeding the input of 2LPNLTF with validation sets which are the regenerated set (6) by $D\left(R_{\text{val}}, H_{\text{val}}, \sigma_0^{\langle\text{val}\rangle}, \mu^{\langle\text{val}\rangle}\right)$ for R_{val} „ R, H_{val} „ H, $\sigma_0^{\langle\text{val}\rangle}$ „ σ_0, $\mu^{\langle\text{val}\rangle}$ „ μ. The set (6) is passed through 2LPNLTF by $R \in$ ¥ for $M \in$ ¥ times until the error on the validation sets is decreasing. Usually, $R_{\text{val}} \in \{0, 1\}$ is taken.

At the final, third stage, the input of 2LPNLTF is re-fed with the training set (5). This is executed for making sure that the pure representatives (5) have not been disassociated from those N wear states. Thus every s -th group of WIF $\left\{x_i^{\langle j_s\rangle}\right\}_{i=1}^{Q}$ is re-associated assuredly with the s -th wear state w_{j_s} by $s = \overline{1, N}$ in FGT (1).

The transition from the initial FGT (1) to EGT

$$\left\{D(R, H, \sigma_0, \mu),\, D\left(R_{\text{val}}, H_{\text{val}}, \sigma_0^{\langle\text{val}\rangle}, \mu^{\langle\text{val}\rangle}\right)\right\}_{m=1}^{M} \tag{7}$$

that would be sufficient for solving the problem (2), requires parameters

$$\left\{S_{\text{SHL}}, R, H, \sigma_0, \mu, R_{\text{val}}, H_{\text{val}}, \sigma_0^{\langle\text{val}\rangle}, \mu^{\langle\text{val}\rangle}\right\} \tag{8}$$

to be ascertained before getting started with the identification of 2LPNLTF. They are selected being based on experience rather than strict methodology [4]. Integer S_{SHL} is specified with Q and N. Some advisable values of parameters (8) were recited in [5, 6]. Mind the term $\sigma_h \cdot \mathbf{\Xi}$ in (6) is responsible for modeling jitter inaccuracies and omissions in statistical data or measurements. The term $\mu \cdot \sigma_h \cdot \mathbf{\Theta}$ in (6) is a model of WIF shift in every state. Therefore, σ_0 characterizes ultimate jitters and μ is ratio between the suspected jitters and WIF shifts.

Tracking wear states could be accomplished with other types of neural networking, used for function approximation. These types are radial basis functions network (RBFN), exact RBFN (ERBFN), generalized regression neural network (GRNN), probabilistic neural network (PNN). However, experiments confirm that effectiveness of tracking wear states with 2LPNLTF (3) is greater in comparison to GRNN an PNN if $\mu > 1$. By that, tracking error rate (TER) of RBFN and ERBFN grows incommensurably high if Q increases.

Discussion

Clearly, the problem (2) cannot be solved exactly. But there are many algorithms of 2LPNLTF (3) identification, bringing maps which are very close (in sense of functional spaces) to the map $\psi_* \in \Psi$ in (2). With properly adjusted parameters $\{S_{\text{SHL}}, \sigma_0, \mu\}$ for EGT (7), these algorithms guarantee fast convergence and well-identified 2LPNLTF (3) as a corollary. Sufficiency of EGT (7) ensues automatically then. While tracking with the well-identified 2LPNLTF, TER is expected minimal [4]. And the forced discontinuity in tracking wear states is natural, because decisions on wear are practically made over finite number of its states (or number of wear threshold values). By the way, decision tree models here are off consideration as they are too complicated in realizability when Q and N are of the order of tens.

Contrariwise, there is no question on realizability of identifying 2LPNLTF (3) and its application after the identification. Particularly, coefficients (4) are updated by the backpropagation algorithm, having a few tens of methods for its implementation. Some of them are fully available within environment MATLAB [5, 6]. Their codes may be freely edited for adapting them to specified problems (2) with parameters (8).

Conclusion

The presented discontinuous tracking model provides controlling the finite set of wear states by the condition that the states' set was statistically tied to the set of representative WIF within FGT (1). If any paired tie of those ones is distinguishable, 2LPNLTF (3) ensures minimal TER even by severe noises, shifts and omissions in WIF groups. When range of wear states embraces all practiced wears, from the "incipiently wear" state up to the state "outworn", 2LPNLTF (3) competes successfully against other approaches. Nonetheless, 2LPNLTF approach is not evolutionary, needing sampled data through the whole tool life. Thus, a further design might be connected with transmitting particular solutions of evolutionary frameworks for FGT (1) in identifying 2LPNLTF (3).

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Романюк В.В. **Дискретна модель відслідковування стану зносу на основі двошарового персептрону з нелінійними передавальними функціями, що навчається на розширеній генеральній сукупності з урахуванням похибок і зсувів у статистичних даних.**

Представляється структура для дискретного відслідковування станів зносу металевого засобу, коли скінченна множина цих станів була статистично пов’язана з множиною репрезентативних факторів, що впливають на знос. Діапазон станів зносу вважається повністю розбитим за цими факторами. Відстежувачем є двошаровий персептрон з нелінійними передавальними функціями. Це — статична модель, на відміну від еволюційних динамічних моделей прогнозування зносу. Її ідентифікація починається з формування початкової скінченної генеральної сукупності, що містить відповідність між факторами впливу та кожним відомим станом зносу. Двошаровий персептрон далі навчається на деякій розширеній генеральній сукупності, чиї елементи є сумою чистих зразків і значень нормальних випадкових величин у двох доданках. Перший доданок моделює флуктуаційні похибки та пропуски у статистичних даних або вимірюваннях. Другий доданок моделює можливі зсуви значень факторів, що впливають на знос, у кожному стані. На завершальному етапі ідентифікації на вхід двошарового персептрону ще раз подаються чисті зразки для того, щоб упевнитися, що вони не були роз’єднані з початково представленими станами зносу. Також наголошено на ймовірній та легкій реалізованості такої моделі відслідковування. Коли діапазон станів зносу буде охоплювати усі види зносу, з якими зіштовхуються на практиці, представлений відстежувач на основі двошарового персептрону буде контролювати стани зносу об’єкта з металевого засобу з мінімізованою похибкою, забезпечуючи незначність недовикористання або перевикористання матеріалів.

Ключові слова: стан зносу, модель відслідковування, статистичні дані, двошаровий персептрон, навчання, ідентифікація, рівень помилок відслідковування, флуктуаційні похибки у даних, пропуски у даних, зсуви у даних.